

Exercício 5

(981)

Para pesos $w \in \mathbb{R}$

$$J(w) = \ell(w) + \lambda \left[\frac{1-\alpha}{2} \|w\|^2 + \alpha \|w\|_1 \right],$$

$$\lambda \geq 0,$$

$$\alpha \in [0, 1]$$

$\ell(w)$ é a perda, soma

4 regularizadores sobre L_2 e L_1

Derivadas de cada termo

Como ℓ é soma

$$d\ell(w) = (\nabla \ell(w))^T dw$$

R_{L_2} (Ridge)

$$R_{L_2}(w) = \frac{\lambda(1-\alpha)}{2} w^T w \Rightarrow$$

$$dR_{L_2} = \lambda(1-\alpha) w^T dw \Rightarrow$$

$$\nabla R_{L_2}(w) = \lambda(1-\alpha) w$$

$$L_1(w) \quad R_{L_1}(w) = \lambda \alpha \sum_{j=1}^d |w_j|$$

$|x|$ não é diferenciável em $x=0$

$$\partial |x| = \begin{cases} \{+1\}, & x > 0 \\ [-1, 1], & x = 0 \\ \{-1\}, & x < 0 \end{cases} \Rightarrow \partial R_{L_1}(w) = \lambda \alpha \text{sign}(w)$$

Subgradiente total do Elástico não

$$0 \in \nabla \ell(w) + \lambda(1-\alpha)w + \lambda\alpha \text{sign}(w)$$

Subgradiente de J é

$$\partial J(w) = \nabla \ell(w) + \lambda(1-\alpha)w + \lambda\alpha \text{sign}(w)$$

$$\frac{\partial J}{\partial w_j} \in \frac{\partial \ell}{\partial w_j} + \lambda(1-\alpha)w_j + \lambda\alpha s_j, \quad s_j \in \text{sign}(w_j)$$

Exercício 5 (pg 3)

Com Logística Binária ($p = \sigma(xw + b)$).

$$\nabla \ell(w) = \frac{1}{n} X^T (p - y), \quad \frac{\partial \ell}{\partial b} = \frac{1}{n} \sum (p_i - y_i)$$

Heurística ~~Q~~

$$\nabla^2 J_{\text{reg}}(w) = \nabla^2 \ell(w) + \lambda (1 - \alpha) I$$

Sub-gradiente direto

$$w \leftarrow w - \eta (\nabla \ell(w) + \lambda (1 - \alpha) w + \lambda \alpha s), \quad s \in \text{Sig}(w)$$

Logit: $z_i = x_i^T w + b$

Probabilidade: $p_i = \sigma(z_i) = \frac{1}{1 + e^{-z_i}}$

Perda média (cross entropy)

$$\ell(w, b) = \frac{1}{N} \sum_{i=1}^N \left[-y_i \log_2 p_i - (1 - y_i) \log_2 (1 - p_i) \right].$$

Elastic net:

$$R(w) = \lambda \left[\frac{1-\alpha}{2} \|w\|_2^2 + \alpha \|w\|_1 \right], \quad \lambda \geq 0, \quad \alpha \in [0, 1]$$

objetivo

$$J(w, b) = \ell(w, b) + R(w)$$

Perdida

Exercício 5 (PB 5)

Derivada da Função Logística

$$\underline{\ell_i = -y_i \log p_i - (1 - y_i) \log(1 - p_i)}.$$

$$\frac{\partial \ell_i}{\partial p_i} = -\frac{y_i}{p_i} + \frac{1 - y_i}{1 - p_i}, \quad \frac{dp_i}{dz_i} = p_i(1 - p_i)$$

$$\frac{\partial \ell_i}{\partial z_i} = \left(-\frac{y_i}{p_i} + \frac{1 - y_i}{1 - p_i} \right) p_i(1 - p_i) = p_i - y_i$$

tendo $z_i = x_i \cdot w + b$

$$\frac{\partial \ell}{\partial w} = \frac{1}{N} \sum_i (p_i - y_i) x_i = \frac{1}{N} X^T (p - y),$$

$$\frac{\partial \ell}{\partial b} = \frac{1}{N} \sum_i (p_i - y_i)$$

$$\nabla_w \ell = \frac{1}{N} X^T (p - y), \quad \frac{\partial \ell}{\partial b} = \frac{1}{N} 1^T (p - y)$$